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Author(s): David P. Anderson, Thanapat Chaisantikulawat, Andrew Tan Khee Guan, Mohamed Kebbeh, Ni Lin, C. Richard Shumway

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CHOICE OF FUNCTIONAL FORM FOR AGRICULTURAL PRODUCTION ANALYSIS

*David P. Anderson, Thanapat Chaisantikulawat, Andrew Tan Khee Guan,
Mohamed Kebbeh, Ni Lin, and C. Richard Shumway*

Economic theory is useful in many aspects of model specification, such as identifying relevant variables for a supply equation or suggesting homogeneity restrictions, curvature requirements, or symmetry restrictions across equations. Theory is seldom sufficient, though, to determine functional form, either a hypothesized true form or a reasonable approximation. Because the validity of statistical tests and inferences are conditional on model specification, the functional form should be appropriate for the specific research use or hypotheses to be tested, capture applicable theoretical concerns, and also allow the data to “speak.” In addition to theoretical considerations, empirical priors (e.g., knowledge about the technology or industry characteristics) and/or model pretesting are often considered by the analyst in choosing a functional form.

The choice of functional form is not a trivial matter. Empirical estimates, including own-price elasticities, elasticities of substitution, returns to scale, and model specification test conclusions are often sensitive to choice of functional form (i.e., Berndt and Khaled; Chalfant; Swamy and Binswanger; Shumway and Lim). Perhaps of greatest importance is the fact that predicted responses of policy analyses using

an inferior functional form may be biased and inaccurate, thus posing serious problems for policy impact analysis. Identifying suitable functional forms before estimating parameters of concern is clearly important.

The most frequently used functional forms in production (and consumption) analyses are second-order Taylor-series expansions, also termed “locally flexible” or just “flexible” functional forms.¹ These forms have a sufficient number of parameters to represent comparative statics at a point without imposing any restrictions across effects (Fuss, McFadden, and Mundlak). Three “flexible” functional forms dominate the recent empirical production economics literature — translog, generalized Leontief, and quadratic. An examination of the 113 published articles cited by Fox and Kivanda and Shumway that estimated static dual models of agricultural production between 1972 and 1993 revealed that one-half used the translog (TL) functional form, one-fourth used the normalized quadratic (NQ), one-eighth used the generalized Leontief (GL), and one-eighth used a variety of other functional forms.

Empirical priors for specifying functional form for an agricultural production model are often limited, both because of the small number of functional form tests conducted and because of differences in findings among them. For example, using different data sets for U.S. agriculture, Gottret failed to reject any of these three functional forms for a restricted profit function, Ornelas, Shumway, and Ozuna failed to reject only the NQ for a restricted profit function, and Chalfant rejected both functional

David P. Anderson is an Agricultural Economist, Livestock Marketing Information Center; Andrew Tan Khee Guan is a lecturer, Universiti Sains Malaysia; and the remaining authors are, respectively, Research Assistant, Graduate Student, Research Assistant, and Professor of Agricultural Economics, Texas A&M University. The authors are listed alphabetically. Senior authorship is shared equally.

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¹They can be expansions of a monotonic transformation of the underlying function, not necessarily of the function itself.

forms (TL and GL) considered for a cost function. Ornelas and Shumway failed to reject the NQ and GL for a restricted profit function of Texas vegetable production. Using U.S. manufacturing data to test the TL and GL, Appelbaum rejected both forms for either a primal or a cost function specification, while Berndt and Khaled failed to reject the GL for their cost function.

All three of these commonly-used flexible functional forms are linear in parameters, so each is convenient to estimate with standard statistical procedures. However, because they maintain various theoretical and practical properties in different ways, one may be more suitable for a specific research objective than another. While they impose no restrictions on comparative statics at a point, each of these functional forms maintains a different set of theoretical restrictions. For example, all are separability inflexible, which means that the function is no longer a second-order Taylor series when separability is maintained in a partition of variables. The TL maintains more restrictions under separability than do the other two functional forms. However, the GL and NQ maintain another restriction even at the point of approximation that the TL does not; i.e., a quasi-homothetic technology (Pope and Hallam; Blackorby, Primont, and Russell).

The functional forms also differ in their convergence properties and in their ability to approximate alternative technologies. For example, expansions in logarithms (such as the TL) have a larger region of convergence than expansions in powers of the variables (such as the NQ or GL) when there is a large dispersion in the data (Driscoll). The TL does not perform as well as the NQ or GL for technologies that exhibit very low elasticities of substitution between inputs, and vice-versa. This can be illustrated by considering the forms of two of these functions when the second-order terms are deleted. In that case, the TL becomes a Cobb-Douglas which maintains an elasticity of substitution among all pairs of inputs of 1.0, and the NQ becomes a linear function which is dual to a Leontief technology with an elasticity of substitution of zero.

Because functional forms have input substitution and returns-to-scale implications, detailed knowledge of the industry under study may shed important light on functional form choice. Such knowledge may come from the researcher's personal experience or from detailed discussions with those involved in the industry. For example, knowledge of the production processes involving the substitutability between sugar and high fructose corn syrup in food processing may direct a researcher to choose a particular functional form. Pre-analysis knowledge of this sort is a better method of choosing a form than convenience only. However, since none of the functional forms dominate the others under all circumstances, additional pretesting may be warranted in this aspect of model specification when there are no strong theoretical or prior empirical reasons to choose one functional form over all others.

The objective of this study is to evaluate the ease of application and empirical performance of a newly-developed, simple, nonnested testing procedure relative to a traditional nested procedure to order rank alternative functional forms. Tests are conducted for choice of functional form using four aggregate agricultural production data sets. While acknowledging the inherent problems associated with use of aggregate data, motivation for the empirical models is a common policy objective — measurement of aggregate responsiveness of output supplies and input demands to changes in expected prices.

Testing Methods

The empirical tests are implemented to discriminate between the three previously-noted functional forms — TL, GL, and NQ — for a dual specification of agricultural production in the United States and three major agricultural states. The statistical procedures used to order rank these functional forms include: (1) the likelihood ratio test for restrictions on two parameters of a Box-Cox transformation which identify the TL, GL, and NQ as special cases; and (2) the likelihood dominance criterion using these forms as nonnested alternatives.

The following quadratic Box-Cox functional form nests the TL, GL, and NQ as well as other first- and second-order Taylor expansions (Appelbaum):

$$Y(\delta) = \alpha_0 + \alpha'X(\lambda) + 0.5X(\lambda)'BX(\lambda) + \epsilon, \quad (1)$$

where Y is normalized profit; X is a vector of output and variable input prices and fixed input quantities; α_0 , α , and β are conformable parameters to be estimated; δ and λ are transformation parameters to be estimated; and ϵ is the error term. $Y(\delta)$ is the transformation $(Y^{2\delta}-1)/2\delta$, and $X(\lambda)$ is the transformation $(X^\lambda-1)/\lambda$.

When $\delta=\lambda \rightarrow 0$, the Box-Cox form becomes the TL functional form:

$$\ln Y = a_0 + a' \ln X + 0.5 \ln X' A \ln X + \epsilon_1, \quad (3)$$

It becomes the GL when $\delta=\lambda=0.5$:

$$Y = b_0 + b' X^{0.5} + 0.5(X^{0.5})'BX^{0.5} + \epsilon_2, \quad (4)$$

and it becomes the NQ when $\delta=0.5$ and $\lambda=1$:

$$Y = c_0 + c'X + 0.5X'CX + \epsilon_3, \quad (5)$$

where a_0 , a , A , b_0 , b , B , c_0 , c , C are conformable parameters; and ϵ_1 , ϵ_2 , and ϵ_3 are error terms.

The nested test procedure permits the TL, GL, and NQ functional forms to be tested against the null of the quadratic Box-Cox form. All can be rejected or not rejected against the null hypothesis. The alternatives can be order ranked by likelihood support against the Box-Cox, but they are not tested against each other.

Conventional nonnested testing procedures can also render an ambiguous conclusion in terms of choosing one of the three functional forms, and they generally do. Because they require two statistics to be computed for each test, one with the form of initial interest as the null hypothesis and a second with the form of initial interest as the alternative hypothesis, each model can be rejected or not rejected against its alternative. The recently-developed likelihood dominance procedure (Pollak and Wales) surmounts this problem of ambiguity in most nonnested tests. When the number of parameters

estimated in each model is the same, as they are in the three functional forms of interest in this article, this criterion renders an unambiguous order ranking of the alternatives. Although no information is provided about the confidence level with which a model is rejected or not rejected, the likelihood values can be used to rank nonnested alternatives by dominance ordering. The form with the highest adjusted likelihood value is preferred.

The likelihood dominance criterion can be related both to nonnested and nested hypothesis testing. When one alternative is accepted and another with the same number of parameters is rejected by this criterion, the model with the higher adjusted likelihood value is always accepted. If a composite model can be formulated that nests each alternative model, as the quadratic Box-Cox does for the alternatives in this article, the likelihood ratio test can be used for model selection. Using the latter test, the probability is zero of selecting a model with a lower likelihood value and rejecting a model with a higher likelihood value that has the same number of parameters. Thus, the model selected by the likelihood dominance criterion would be the same as the one selected by the likelihood ratio test.

This means that order ranking by the likelihood dominance criterion is the same as by the likelihood ratio test of the nested alternatives within the quadratic Box-Cox, and it is not necessary to estimate the composite model. Although alternatives with different numbers of parameters are not examined in this article, the same is true for them when the likelihood dominance test statistic is outside the narrow indecisive region. In that case, the likelihood dominance criterion (LDC) prefers H_0 to H_1 if:

$$L_1 - L_0 < \frac{[C(k_1 + 1) - C(k_0 + 1)]}{2}, \quad (5)$$

where L is the adjusted loglikelihood value, $C(\cdot)$ is the critical value of $\chi^2_{\alpha,(\cdot)}$, k is the number of independent parameters estimated, 1 and 0 identify hypothesis numbers where the hypotheses are ordered such that $k_1 > k_0$, and (\cdot) identifies the degrees of freedom. The LDC prefers H_1 to H_0 if:

$$L_1 - L_0 > \frac{[C(k_1 - k_0 + 1) - C(1)]}{2}. \quad (6)$$

The criterion is indecisive between H_0 and H_1 only if:

$$\frac{[C(k_1 - k_0 + 1) - C(1)]}{2} > \frac{[C(k_1 + 1) - C(k_0 + 1)]}{2}. \quad (7)$$

Pollak and Wales applied the likelihood dominance criterion to an evaluation of alternative demand systems. They found a clear preference in each of five pairwise comparisons even though the number of parameters differed within each pair.

An important benefit of the likelihood dominance criterion as a testing procedure over the nested tests is that larger-dimensional models (i.e., models with more variables) can be estimated. Since each of the three forms of interest is linear in parameters, no convergence problems are faced in obtaining their parameter estimates as may occur in obtaining parameter estimates with nonlinear models such as the Box-Cox. More variables can be included in the model, so less commodity-wise aggregation of data is required. And, unlike conventional non-nested tests, a clear order ranking of alternative models is generally obtained.

The likelihood dominance criterion can also be related to model selection criteria such as Akaike's information criterion, Amemiya's prediction criterion, or Schwarz's criterion (Judge et al.). They often give the same result with regard to order ranking of alternative model specifications. However, while these criteria are somewhat ad hoc and "have no firm basis in theory" (Greene), the likelihood dominance criterion rests on a sound analytical foundation (as noted above) that is consistent with a classical statistical approach to hypothesis testing.

Our implementation of the likelihood dominance criterion differs from this Box-Cox test in two ways: (1) less aggregated data are used; and (2) the system of first-derivative equations is estimated rather than the profit function.² By Hotelling's lemma, these equations

are the output and input profit share equations for the TL:

$$s_i = a_i + \sum_j a_{ij} \ln x_j + \epsilon_{1i}, \quad (8)$$

$$i = 1, \dots, m-1,$$

and the output supply and input demand equations for the GL and NQ, respectively:

$$z_i = \frac{(b_0 + \sum_j b_{ij} x_j^{0.5})}{2x_i^{0.5}} + \epsilon_{2i}, \quad (9)$$

$$i = 1, \dots, m-1,$$

and

$$z_i = c_0 + \sum_j c_{ij} x_j + \epsilon_{3i}, \quad (10)$$

$$i = 1, \dots, m-1,$$

where s_i is the profit share of netput i , z_i is the quantity of netput i (positive if i is an output and negative if i is an input), ϵ is the error term, and m is the number of variable netputs. Each price is normalized by the price of netput m . Because the dependent variables for the TL are different from those for the GL or NQ, their log-likelihood function value must be adjusted by the Jacobian (i.e., the logarithm of the absolute value of the determinant of $\partial \epsilon_i / \partial z$ is added to equation (8)'s log-likelihood function value). This adjustment is essential for consistent comparison since the dependent share variables of the TL system are functionally related to the dependent quantity variables of the GL and NQ systems.

Estimation

Assume that an aggregate restricted (short-run) profit function exists for each data set. Individual producers are assumed to be price-takers who seek to maximize expected profits. If the profit function were written for such an individual firm, it would be linear homogeneous, convex, and monotonic in prices. If the function were also twice continuously differentiable, the parameters of the output supply and input demand (or share) equations in the system

²For greater efficiency of the estimates, the system of estimation equations could also have included the respective form of the profit function.

models would be symmetric. When data are aggregated, even consistently, there is no assurance that the aggregate model has the same properties as the firm-level model. Therefore, neither convexity nor monotonicity in prices is maintained in the estimation. On practical grounds, linear homogeneity and symmetry are maintained. Homogeneity is maintained by normalization in all models and data sets. Symmetry is maintained by linear restrictions in the system models. These restrictions do not alter the flexibility of any of the functional forms examined except that each is now a second-order Taylor-series expansion in relative prices.

Assuming the error term in equation (1) is additive and normally and identically distributed with mean zero and constant variance, the parameters of the quadratic Box-Cox are estimated by nonlinear least squares after carrying the dependent variable transformation to the right-hand side of the equation. This leaves normalized profit as the dependent variable. The estimation procedure yields maximum likelihood estimates. The parameters are estimated independently for each data set: (1) without restrictions; and (2) with each set of restrictions on δ and λ that represent the functional forms in equations (2) to (4). The likelihood ratio statistic is computed for each set of restrictions. This statistic is distributed as a chi-square under the null hypothesis that the true parameters are the unrestricted Box-Cox estimates.

Assuming the error terms in each system of equations, (8) to (10), are additive and normally- and identically-distributed, with zero mean and a constant contemporaneous covariance matrix, the parameters of the first-derivative equations are estimated by iterative seemingly unrelated regression (ITSUR). Parameter estimates are iterated until convergence of the covariance matrix is achieved. This procedure is asymptotically equivalent to the maximum likelihood method of estimation (MLE). As a result, large sample properties of MLE are obtained. In addition, the translog estimates are invariant to the choice of equation omitted.

Data

This study utilizes one aggregate U.S. and three state-level agricultural data sets. The

aggregate U.S. data are from Ball and are an annual series for the period 1948 to 1989, a total of 42 observations. They represent a comprehensive set of extensively revised and updated aggregate output and input quantities and prices that are organized into the same 12 categories reported in Ball. They consist of five output categories (livestock, fluid milk, grains, oilseeds, and other crops), and seven input categories, five of which (durable equipment, farm-produced durables, hired labor, energy, and other purchased inputs) are treated as variable inputs in the system models and two (real estate and self-employed labor) are treated as fixed inputs in those models.

The state-level data are annual series compiled by Robert Evenson, Wallace Huffman, and Christopher McIntosh for three major agricultural states (California, Florida, and Iowa) for the period 1951 to 1986, a total of 36 observations each. The data in each state include quantities and prices for an exhaustive array of output and input items. For the system models, outputs are aggregated into four categories (grains, fruits and vegetables, other crops, and livestock), variable inputs are grouped into six categories (capital services, hired labor, fertilizer, operating machinery, pesticides, and miscellaneous variable inputs), and fixed inputs include family labor and land.

In the quadratic Box-Cox models, outputs in each data set are aggregated into three categories (grains, other crops, and livestock), variable inputs are aggregated into one category, and fixed inputs (self-employed or family labor, and real estate or land) are aggregated into one category. The dependent variable, profit, is calculated as the sum of output revenues minus expenditures on variable inputs.

Divisia indices are used to compute all aggregate price indices. Quantity indices are computed by dividing category receipts or expenditures by the respective price index.

The price of variable inputs is used to normalize profit and prices in the quadratic Box-Cox model for each data set. The price of other purchased inputs is the normalizer in the system models for the United States. The price of miscellaneous variable inputs is the normalizer in the system models for each state. Thus, the

quadratic Box-Cox models include three normalized prices, one fixed input quantity, and their squared and interaction terms as regressors. The system models include nine normalized prices and two fixed input quantities as regressors in each output supply and input demand equation.

Empirical Results

The nested test results for each data set are reported in Table 1. Each of the three popular flexible functional forms was tested using the likelihood ratio test. At the 0.05 significance level, all three functional forms were rejected against the quadratic Box-Cox for the United States, none were rejected for California, the GL and NQ were rejected for Florida, and the TL and NQ were rejected for Iowa.

With regard to ordering the nested functional forms based on likelihood support, the loglikelihood function values reported in Table 1 can be used directly by the likelihood dominance criterion since the dependent variable was the same in the estimated model for each functional form. These results indicate that the TL is preferred among the three flexible forms for the aggregate U.S. data, and the NQ is least preferred. However, the difference in the statistics between the NQ and GL is small compared to the difference between the GL and TL for this data set. The TL is also the preferred form, and the NQ is least preferred for the California and Florida data sets, but the difference in statistics between any of the flexible forms in California is trivial. For the Iowa data set, the GL is the preferred form, and the TL is least preferred.

In an attempt to provide a possible rationale for these differences in preferred functional forms for the different data sets, we focus on the fundamental differences in agricultural production in these geographic entities. While agricultural production in California, Florida, and the United States is highly diversified, Iowa crop agriculture can be characterized as predominantly a corn-soybean rotation. The established crop rotation among few crops along with the farm program's corn base acres may render lower elasticities of substitution and help

explain the preference for the GL functional form in this state.

However, before attributing too much to this difference in production characteristics, one should examine the statistics reported in Table 2. Here, the loglikelihood function values for the three functional forms estimated as systems of equations using the less aggregated data are presented. Likelihood values of the translog have been adjusted by the Jacobian of the share equations with respect to the netput quantities.

The likelihood value of the TL system of equations is highest for each of the disaggregated data sets. By the likelihood dominance criterion, the TL is the preferred functional form for each data set. The NQ is least preferred for the United States, California, and Florida data sets. In contrast to the Box-Cox nested test using more aggregated data, the GL is least preferred for the Iowa disaggregated data set with the system of equations. Likelihood values for the GL and NQ are consistently similar in all four data sets with both tests, but the TL is preferred for each data set. It is not surprising that the likelihood values for the GL and NQ would be most similar since they are expansions around the original independent variables and their square roots, both of which can be represented by powers of the variables (1.0 and 0.5), while the TL is an expansion around the logarithms of all variables.

As one might expect, the choice of functional form is likely to be both model and data specific. While the translog was selected for each of the four data sets based on likelihood dominance with the less aggregated data, it was not selected for Iowa with the aggregated data. In contrast, Shumway and Lim; Ornelas, Shumway, and Ozuna; and Ornelas and Shumway found the TL to be generally inferior to either the GL or NQ for their agricultural data. Appelbaum as well as Berndt and Khaled also found the TL to be less preferred than alternative forms for their manufacturing data. The sensitivity of these findings is further documented by the fact that Shumway and Lim and Ornelas, Shumway, and Ozuna both used U.S. data similar to the data used in this study. Differences between the two data sets included extensive revisions in the input series and 10

Table 1. Nested Functional Form Test Results

Data Set	Functional Form	Log-likelihood Function Value	Likelihood Ratio Test Statistic ^a
United States	Quadratic Box-Cox	-409.26	
	Translog	-423.68	28.84
	Generalized Leontief	-502.89	187.26
	Normalized Quadratic	-504.73	190.94
California	Quadratic Box-Cox	-199.51	
	Translog	-199.56	0.10
	Generalized Leontief	-200.12	1.22
	Normalized Quadratic	-200.52	2.02
Florida	Quadratic Box-Cox	-189.36	
	Translog	-191.20	3.68
	Generalized Leontief	-195.72	12.72
	Normalized Quadratic	-196.83	14.94
Iowa	Quadratic Box-Cox	-215.80	
	Translog	-221.78	11.96
	Generalized Leontief	-217.81	4.02
	Normalized Quadratic	-218.83	6.06

^aCritical value at the 0.05 significance level is 5.99.

Table 2. Nonnested Functional Form Test Results

Data Set	Functional Form	Log-likelihood Function Value ^a
United States	Translog	-1,583.42
	Generalized Leontief	-3,001.01
	Normalized Quadratic	-3,001.08
California	Translog	-1,471.75
	Generalized Leontief	-1,612.21
	Normalized Quadratic	-1,616.90
Florida	Translog	-1,150.63
	Generalized Leontief	-1,305.90
	Normalized Quadratic	-1,327.78
Iowa	Translog	-1,223.79
	Generalized Leontief	-1,529.43
	Normalized Quadratic	-1,528.09

^aAdjusted by the Jacobian of the vector of dependent share variables in equation (8) with respect to the vector of quantity in equations (9) and (10).

additional observations in the data used in this study, maintenance of constant returns-to-scale in construction of the earlier data set, and only one fixed input plus time in their models. Ornelas and Shumway used state-level data for Texas that was similar to the data used in this study and examined both nested test results and predictive performance of alternative functional forms. The NQ was preferred by the nested test,

followed in turn by the GL and TL. The GL was the best out-of-sample predictor, followed in turn by the TL and NQ.

Conclusions

Important empirical conclusions of economic analyses are often sensitive to choice of functional form for the estimation equation(s).

Preferred functional form depends on a variety of things, including theory, underlying technology, research objective, empirical priors, range of approximation and/or convergence desired, model, and data. Among equally suitable *a priori* functional forms, the most common method of allowing the data to help select a form has been nested testing procedures. Typically, the Box-Cox transformation has been used as the vehicle for nesting alternative functional forms of interest. Nonnested tests (e.g., J, JA, or Cox tests) and predictive accuracy have also been used as criteria. Both the nested and nonnested tests are often cumbersome to implement and frequently render ambiguous conclusions about the alternative functional forms of primary interest.

This article has focused on the use of the recently-developed likelihood dominance criterion (Pollak and Wales) as a means of order ranking alternative functional forms based on the data. In addition to being consistent with a classical statistical approach to hypothesis testing, this criterion is easier to implement than either the standard nested or nonnested testing procedures. Estimation of a composite model that nests the alternatives is not required, so larger-dimensioned problems can be modeled. Neither does it require conducting pairs of tests (i.e., by reversing the null and alternate hypotheses) as required in conventional nonnested hypothesis testing. A clear ordering of all alternatives having the same number of parameters and a clear ordering of most alternatives having an unequal number of parameters are rendered.

The ease of application and empirical performance of the likelihood dominance criterion for functional form selection were evaluated using four aggregate agricultural production data sets and two separate models. One data set was for the United States and three were for individual states. One model was a normalized restricted profit function for highly aggregated data. The other model was a system of output supply and input demand (or share) equations for less aggregated data. The first was estimated as a Box-Cox model, and tests for three alternative nested functional forms were

conducted. The second model was estimated for each of the three alternative functional forms, and dominance ordering was used to order rank the alternatives. The likelihood dominance criterion can be used to order rank alternatives estimated with either procedure. No information is provided about the confidence level with which a model is rejected or not rejected, but the adjusted likelihood values can be used to rank nonnested alternatives.

Because preferred functional form appears to be both data and model specific and because empirical results are often highly sensitive to choice of functional form, it is important that alternative functional forms be examined. Empirical tests for choice of functional form should perhaps be considered as a part of standard pretests for model specification in production analysis. Given its simplicity and its ability to provide an unambiguous ranking of most alternatives, the nonnested likelihood dominance procedure is both suitable and convenient for this purpose.

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